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Multiobjective site selection model for emergency shelter facilities in urban areas

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Abstract

Industrial and economic development is primarily applied to densely populated urban areas. If a sudden disaster occurs in such areas, the consequences can be severe. Shelter facility location affects the implementation of postdisaster relief work. This study explored residents' perceived utility of evacuation time, their risk utility for road blocking, and the cost factors associated with constructing shelter facilities in the context of governance. A location model for emergency shelter facilities in cities was established on the basis of the aforementioned factors. Because the resolution of the random-weighted genetic algorithm (RWGA) is susceptible to influence from random weights, a robustness random-weighted method (RRWM) was developed. The validity and feasibility of the location model were examined through numerical analysis. Finally, the convergence of the RRWM was analyzed and compared with that of the RWGA and a single-objective genetic algorithm. The results revealed that the proposed algorithm exhibited satisfactory performance and can assist in evaluation and decision-making related to the selection of urban shelter facility locations.

Keywords: Sudden urban disaster, Location problem, Multiobjective programming

1. Introduction

Climate change and social disruption may lead to natural or artificial disasters such as typhoons, earthquakes, and nuclear accidents, all of which can substantially affect urban economies [1]. After a sudden large-scale disaster or major accident, the affected population must immediately seek refuge in safe and shelter facilities. Therefore, the selection of shelter facility locations is crucial to urban disaster prevention and urban development, and the locations of such facilities should be based on pedestrian patterns.

Existing places of refuge should be selected as locations for facilities with short- and medium-term sheltering functions. Resources can then be allocated to improve and reconstruct these facilities and to stockpile supplies in order to meet safety standards. Therefore, numerous factors must be considered during the site selection process. Accordingly, the "Easy-to-Do" program of the National Science and Technology Center for Disaster Reduction (Taiwan) considers the physical environment, shelter-related facilities, and factors such as distance to a sheltered facility (https://easy2do.ncdr.nat.gov.tw/easy2do/). Several studies have suggested that the time required to seek refuge is a critical factor for site selection [2, 3].

However, unsuspecting city residents may be influenced by psychological factors such as panic and fear during a disaster because of the chaos caused by the interruption of urban traffic networks and the breakdown of communication. Lin et al. [4] have thus suggested that panic following a disaster hinders individual judgment. The public may not act entirely rationally when confronted by an unexpected disaster [5]. Consequently, according to prospect theory [6, 7], effective decision-making behavior is based on bounded rationality under an emergency. However, an increasing number of studies evaluating shelter facilities have focused on residents' subjective feelings, including their satisfaction with evacuation time [8]. Shelter distance and evacuation time alone may not explain residents' perspectives regarding shelter facilities following a disaster. Hence, residents' perceived evacuation time must be considered to accurately determine their choice of shelter facilities following a disaster.

Because road networks may be blocked or destroyed following a disaster, the urban space undergoes drastic changes. When residents with bounded rationality are confronted by these changes, they may experience difficulty in making accurate risk assessments while on the road. The risk of road network blockage affects the safe

travel of residents to shelter facilities; therefore, this phenomenon should be considered during site selection [8]. Moreover, medium- and short-term shelter facilities should be constructed even if no urban disasters are expected. In the context of budgeting [1], resources should be allocated to reconstruction and the establishment of shelter environments that conform to disaster resistance standards.

The aforementioned factors directly affect the efficiency of shelter selection among people affected by a disaster. Accordingly, this study considered the effects of the aforementioned factors on postdisaster situations. Such factors include the perception of the time required to reach a shelter, the risk of using roads to reach the shelter, the cost of establishing shelter facilities, and the accommodation limitations of the shelter. The study developed a multiobjective model of site selection for urban shelter facilities. This model considers the aforementioned factors; therefore, when an unexpected disaster occurs, shelter facility information should be transmitted to mobile phones and other devices. This method for disseminating relevant information eliminates the need for the public to make decisions regarding where to find shelter.

A multiobjective problem involves a trade-off between various objectives. The optimal solution for this problem can be obtained using the random-weighted genetic

algorithm (RWGA; [9]). However, because the RWGA is easily affected by weight changes, the quality of its solutions is inconsistent. Therefore, we incorporated the elitism method into the RWGA to develop a robustness random-weight method (RRWM). In the RRWM, the coverage and distribution of the solution set are used to evaluate the solution and thus obtain improved solution performance. The rest of this paper is organized as follows. First, the research topic is analyzed and explained. Second, relevant studies are reviewed. Third, the proposed multiobjective site selection model for urban shelter facilities is described. Fourth, a robust stochastic weighting method is proposed for the developed model, and a method for evaluating the multiobjective solution set is presented. Fifth, an example network is described for Zhongzheng District in Taipei City. This network was used to test the accuracy and applicability of the proposed model. The results obtained using the proposed model were compared with those obtained using other algorithms in the aforementioned example; the comparison results indicated that the proposed model outperformed the other algorithms. Finally, the conclusions of this study, applications of the proposed model, and directions for future research are presented.

2. Problem analysis and literature review

2.1. Refuge location selection model

Current et al. [10] used a multiobjective approach to solve a site selection problem; since their study, such approaches have been extensively used to solve site selection problems in various fields. Fan [11] obtained the relative weights of various assessment factors by using an expert questionnaire and the analytic hierarchy process. On the basis of these weights, the researchers established four assessment items with subcriteria such as structural safety, location, traffic, living function, and service for flood refugees. These subcriteria can serve as a reference for the assessment of shelter facilities for flood victims.

Location problems are typically divided into four types: P-median, P-center, location coverage, and maximum coverage location. Farahani et al. [12] comprehensively examined the models, solutions, and applications of coverage problems for facility site selection. To solve a site selection problem for disaster emergencies, Li et al. [13] proposed a coverage location model and applied various algorithms. Hobeika [14] considered the travel time between residences and storm shelter facilities and proposed a site selection model to minimize the travel time.

Sherali et al. [15] studied evacuation facilities for flood disasters and proposed a

bilevel planning model: The upper-level problem is a site selection problem for evacuation facilities, and the aim is to minimize the time required to reach the shelter. The lower-level problem is related to the route between the residence and the shelter. They used a genetic algorithm (GA) to solve this two-level problem.

On the basis of a case study of the 2010 Chile earthquake, Pérez-Galarce et al. [16] considered the challenge of earthquake disasters in urban areas. They developed a flexible model for optimizing the service quality of shelter facilities after disasters. This model also enables the provision of appropriate shelter and medical assistance through improved shelter facilities. Boonmee et al. [17] discussed emergency models for facilities such as distribution centers, warehouses, shelters, and medical centers. They examined each type of facility, data model, and disaster. Accordingly, they proposed a model that can be used to select sites for shelter facilities according to the characteristics of the disaster, the needs of the victims, and the principle of equity.

2.2. Objective and limiting factors for shelter site selection

After an urban disaster, the external environment changes dramatically. Because the public's perception of these environmental changes influences their behavior, such changes should be considered in shelter site selection processes. Moreover, panic after

a disaster reduces the ability of victims to make sound judgments, which leads to imperfect rationality [5] or bounded rationality [6, 7]. Therefore, site selection for shelter facilities may consider the bounded rationality of disaster victims according to their perceptions of the external environment. If a shelter location is selected solely according to its distance from the disaster area [18] and without consideration of public perception, then the selection policy may not match the behavior of the affected individuals. The suitability of a shelter facility location is reflected in the victims' levels of perception at different sites [19]. For a given shelter facility, people in different affected areas have different levels of satisfaction. The linear time satisfaction function is the simplest method for converting evacuation time or distance into time satisfaction [8, 20]. Therefore, maximizing the public perception of the time required to reach a shelter after an urban disaster was the primary model objective in the present study.

Urban road networks may be interrupted by urban disasters, which can lead to building collapses or the destruction of underground chemical pipelines. Therefore, the risk of urban road network blockage should be considered when selecting shelter facility sites, and the impact of this risk should be minimized. To identify the factors

influencing shelter site selection, Zhu and Wang [21] have improved the conventional spatial location selection problem by establishing a road emergency evacuation index and a road risk coefficient to quantify road network risks. In addition, Hsu and Lu [22] determined the risk of earthquake-induced road blockages. They created a joint utility function by combining this risk with the influence of traffic load on traffic congestion to obtain the path of least risk for earthquake relief. By combining a geographic information system with a traffic assignment function, they established an application model for disaster relief path selection. Shen et al. [8] considered human vulnerability to toxic chemical gases, road accessibility probability, and satisfaction with evacuation time as influencing factors for the selection of shelter sites in a chemical industry zone. They established a site selection model according to the maximum road accessibility probability.

After an appropriate urban shelter site is selected from various alternatives (excluding potentially dangerous sites), resources are invested to construct facilities according to the required medium- or short-term functions of the site. Therefore, the cost of construction and the distance from the affected area are factors that warrant consideration in shelter site selection processes for construction. Karatas [23] have

argued that the cost of facility construction affects site selection. Chen et al. [24] considered construction cost and asylum setup benefits as target factors in the selection of an emergency shelter site. They proposed two site selection objectives—namely minimizing total distance and minimizing construction cost—and established three hierarchical site selection models for emergency shelters.

The capacity limitation of a shelter facility is a crucial modeling constraint. Current and Storbeck [25] established location coverage and maximum coverage models for selecting locations with capacity constraints. Wu et al. [26] proposed a coverage model for site selection under capacity and construction cost constraints. To evaluate emergency evacuation strategies for major urban emergencies, Li et al. [19] comprehensively considered shelter capacity and the uneven distribution of the urban population; they suggested that effective strategies should ensure that shelter capacity is not exceeded and that the distance between residences and shelters is minimized. Their results indicated that the model with capacity constraints was superior to that without such constraints because it could more accurately reflect the real-life situation of the problem.

2.3. Multiobjective programming models and related algorithms

Multiobjective programming is a mathematical method for solving decision problems with multiple objectives through linear programming. The aim of this approach is to identify the optimal solution within the constraints of limited resources and conflicting objectives. Kuhn and Tucker [27] deduced the optimality conditions for the existence of effective solutions, which laid the foundation for multiobjective theory. Multiobjective programming includes multiple quantifiable objective functions with well-defined constraints. The mathematical programming component evaluates trade-offs between the objectives and obtains a set of noninferior solutions or nondominated solutions. Multiobjective optimization has been extensively studied and applied in numerous fields. Shukla and Deb [28] divided methods for solving multiobjective optimization problems into two categories: traditional and nontraditional methods, among which the non-traditional methods developed evolutionary multiobjective optimization (EMO) is based on the concept of natural selection. EMO identifies multiple Pareto optimal solution sets in the space of feasible solutions. The graph surface formed by all nondominant solutions is called the Pareto front .

Alçada-Almeida et al. [29] verified evacuation plan safety by using a

multiobjective planning approach; this approach involves the use of a geographic information system and a multiobjective programming model in the design of a decision support system. Zhou et al. [30] proposed a multiobjective model for selecting the sites of urban shelter facilities. The model incorporates the maximum weighted minimum distance as well as the weighted and maximum coverage areas for shelter facilities. Coutinho-Rodrigues et al. [31] developed a multiobjective planning model for evacuation path and shelter facility locations by using six objectives, including risks associated with path and shelter locations, evacuation path length, and the final evacuation time from residences to shelters. Because of the complex environments people must traverse during urban disasters, researchers have considered various attributes, characteristics, and objectives in the development of disaster models. Therefore, the locations of shelter facilities have often been interpreted and expressed within the context of multiobjective planning.

Most relevant algorithms are based on evolutionary algorithms (EAs). Because of their suitability for solving complex problems, search algorithms have also been applied to various optimization problems [32]. In EAs, adaptive individuals with diverse genetic characteristics can be selected from a population according to their

environmental fitness. EAs can be categorized according to three design choices, namely individual representation, parent selection, and operating mode. Evolutionary programming, evolutionary strategies, and GAs are examples of EAs, with GAs being the most common EAs.

Multiobjective GAs (MOGAs) focus on the development of adaptive functions. Numerous MOGAs have been developed to solve multiobjective problems with different characteristics on the basis of the evaluation of adaptive functions. Konak et al. [33] categorized MOGAs according to their adaptive functions and algorithm programs and compared the advantages and disadvantages of these algorithms. Among these methods, the aggregation function was the first to be developed and is the most direct approach for solving multiobjective optimization problems. In this method, a single-objective solution is obtained for the multiobjective problem by adjusting the weight coefficient through combination or aggregation. The RWGA proposed by Murata and Ishibuchi [9] are based on weight summation. Murata and Ishibuchi [9] compared the RWGA with the vector-evaluated GA (VEGA). Their results revealed that the RWGA yielded more optimal solutions than did the VEGA.

2.4. Comprehensive evaluation and analysis

In the present study, the public perception of evacuation time, road availability, and facility construction cost in the context of urban disasters were considered as factors affecting site selection. The aim of a site selection strategy should be the maximization of the utility of perceived evacuation time, maximization of road accessibility, and minimization of the construction cost of facilities. On the basis of the aforementioned literature review, this study conducted a comprehensive evaluation, which is described as follows:

1. After an urban disaster, victims typically move to shelter facilities by walking quickly. The distance from residences is typically the main factor considered when planning facility locations. Accordingly, the current study considered the P-median problem for site selection. Service time satisfaction [8, 20] and the utility function proposed by Fiedrich et al. [34] were combined to transform the simple distance factor into the perceived utility of evacuation time.
2. The three objectives established for the proposed model were to maximize the perceived utility of evacuation time, maximize the utility of network access risk, and minimize the cost of shelter construction. We considered these three objectives to maintain the functions necessary for the postdisaster life of asylum

seekers within the capacity of shelter facilities. Therefore, a multiobjective model was established for selecting emergency shelter facility sites for urban disasters.

3. The proposed programming model for solving the multiobjective problem is based on trade-off solutions. On the basis of the aforementioned studies, the RWGA, which is based on the MOGA, was adopted for the programming model. Moreover, this algorithm was improved to facilitate the resolution of the relevant multiobjective problem.

3. Research model construction

In the conventional maximum coverage problem, the aim is to minimize the average travel distance between the demand and service nodes. Therefore, demand nodes that are located outside the maximum service distance from a given service node must be covered by other service nodes. However, in the context of traveling to shelter facilities after disasters, the service level of shelter facility j is not limited to its spatial distance from disaster site i. The evacuation time t_{ij} between disaster site i and shelter facility j should be the main basis for assessment. Therefore, $t_{ij} \leq L_i$ indicates that victims at disaster node i feel safe traveling to shelter node j. The term L_i denotes the longest time that people at disaster node i are willing to accept when evacuating to

shelter facility j.

Disaster victims decide to leave the affected area to seek shelter according to their expectations of the facility and environmental factors. In this case, distance is the main consideration in shelter site selection processes, and the travel time between the disaster site and the shelter facility is ignored. However, in practice, urban spaces change substantially after disasters, and the members of the public are in a state of bounded rationality. Therefore, an accurate perception of the distance to shelter facilities may be difficult for the public to obtain.

Herein, $U(t_{ij})$ is defined as the perceived utility of evacuation time between disaster node i and evacuation facility j, and $L_{i,desired}$ is defined as the maximum evacuation time that victims at disaster node i can accept for traveling to shelter facility j. In an emergency, victims are expected to travel to shelter facilities in the shortest possible time because they are likely to be highly anxious; in addition, evacuation time is influenced by the disaster situation. According to the evacuation time defined by Ren et al. [35] and the graded mean integration representation method proposed by Chou et al. [36], the maximum acceptable evacuation time can be defined as follows:

$$L_{i,desired} = \frac{t_{ij,optimistic} + 4t_{ij} + t_{ij,longest}}{k} \quad , k = 6 \tag{1}$$

where $t_{ij,optimistic}$ is the most optimistic time from disaster node i to shelter facility j (e.g., the shortest possible time to complete an evacuation activity), t_{ij} is the actual evacuation time from disaster node i to shelter facility j, and $t_{ij,longest}$ is the longest evacuation time from disaster node i to shelter facility j. Therefore, the psychological factors of the affected people are modeled as a trade-off between t_{ij} and $t_{ij,longest}$ (i.e., $L_{i,desired}$), which is used to evaluate their perceived evacuation time. To normalize perceived evacuation time, this factor is transformed into a utility value between 0 and 1. The utility function for perceived evacuation time is presented in Eq. (2) [7, 19].

$$U_a(t_{ij}) = \begin{cases} 1 & if \;\; t_{ij} \leq L_{i,desired} \\ \left[1 - \frac{t_{ij} - L_i}{\left(\underset{ij}{\text{Max}} \;\; t_{ij} - L_i\right)}\right]^{k_i} & if \;\; L_i < t_{ij} \leq t_{ij,longest} \\ 0 & if \;\; t_{ij} > t_{ij,longest} \end{cases} \tag{2}$$

We can assume that the utility function of perceived evacuation time is nonlinear. The value of k_i can be considered the sensitivity coefficient for evacuation time. This parameter represents the sensitivity of people in different regions (e.g., cities and rural areas) to the evacuation time. The higher the value of k_i is, the higher the gradient of

the utility function of perceived evacuation time is, which indicates greater time sensitivity. Ma et al. [20] suggested that k_i should be between 0.5 and 1.5. The effect of sensitivity coefficient k_i is illustrated in Figure 1. Individual perceptions of evacuation time can vary even in the same area. However, the aim of the present study was not to estimate individual heterogeneity. Therefore, the utility function of perceived evacuation time is defined according to the assumption of homogeneous sensitivity coefficients.

On the basis of the suggestions provided by Shen et al. [7] and Hsu and Lu [21], the utility of the risk of a roadblock for a road section after a disaster can be defined as follows. The risk of a roadblock is defined as the probability of a roadblock due to the collapse of buildings and to other factors influencing the road section. For a known roadblock risk, a utility function is used to convert the risk value into a utility value. Herein, the utility function for roadblock risk is a decreasing exponential utility function. If the roadblock probability is 0, the road section is unaffected, and the utility value is 1. If the roadblock probability is 1, the road section has been severely damaged, and its safety and reliability are extremely low; thus, the utility value is 0. The utility function of roadblock risk for road section a is defined as follows:

$$U_a = -0.198 + 1.198e^{-R_a} \qquad 0 \le R_a \le 1 \quad , \forall a \in A \tag{3}$$

where R_a is the roadblock probability for road section a. The utility value of the roadblock risk for a section reflects the safety and reliability of the road. It can also be considered to be the probability of being able to pass through a road section. The higher the utility of the roadblock risk is for a road section, the higher is the probability of disaster victims being able to use this section to reach shelter facilities. Therefore, on the basis of the discussion on road passability by Shen et al. [7], the utility of the roadblock risk of road section a is defined as the passability of road section a, as presented in Eq. (4). Moreover, u_k^{ij} is defined as the utility value of roadblock risk for path k from disaster node i to shelter node j. Similarly, p_k^{ij} is defined as the probability that path k can be used to travel from disaster node i to shelter node j. Therefore, the risk of a roadblock in a road section and the utility value of the risk of a roadblock are defined as follows:

$$U_a = P_a \qquad \forall a \in A \tag{4}$$

$$p_k^{ij} = \prod_{a=1} P_a \delta_{ak}^{ij} \qquad \forall i \in I, j \in J, k \in K \tag{5}$$

$$u_k^{ij} = p_k^{ij} \qquad \forall i \in I, j \in J \tag{6}$$

where δ_{ak}^{ij} indicates whether road section a is included in path k from disaster node i to shelter node j. If road section a is included in path k, then δ_{ak}^{ij} = 1; otherwise, δ_{ak}^{ij} = 0. To simplify operations, Eq. (5) can be rewritten as follows by taking logarithms on both sides:

$$\log p_k^{ij} = \log P_1 \delta_{1k}^{ij} + \log P_2 \delta_{2k}^{ij} + ... + \log P_a \delta_{ak}^{ij} \qquad \forall i \in I, j \in J, k \in K \quad (7)$$

Eqs. (6) and (7) can then be combined as follows:

$$u_k^{ij} = \sum_a \log P_a \delta_{ak}^{ij} \qquad \forall i \in I, j \in J, k \in K \quad (8)$$

Finally, the cost of constructing shelter facilities is based on the investment of resources at sites that meet a set of conditions. If the number of shelter facilities is unknown, the number of facilities should be determined in terms of their construction costs. At least one facility should be constructed. The number of shelter facilities to be constructed depends on their construction costs, and this number cannot exceed the maximum number of alternative sites (N).

On the basis of the problem description, the multiobjective model for the selection of urban shelter sites comprises three objectives, as presented in Eqs. (9)–(11): maximizing the utility of perceived evacuation time (Objective 1), maximizing the utility of roadblock risk (Objective 2), and minimizing the construction cost of shelter

346 facilities (Objective 3). These objectives are subject to various restrictions, which are

347 presented in Eqs. (12)–(23).

348 $$\text{Max } Z_1 = \sum_{i \in I} \sum_{j \in J} h_{ij} f\left(t_{ij}\right) y_{ij} \quad (9)$$

349 $$\text{Max } Z_2 = \sum_{i \in I} \sum_{j \in J} u_{ij} y_{ij} \quad (10)$$

350 $$\min Z_3 = \sum_{j \in J} C_j x_j \quad (11)$$

351 Subject to $$\sum_{j \in J} y_{ij} \geq 1 \quad \forall i \in I \quad (12)$$

352 $$\sum_i y_{ij} \leq n x_j \qquad \forall i \in I,\ j \in J \quad (13)$$

353 $$1 \leq \sum_{j \in J} x_j \leq N \quad \forall j \in J \quad (14)$$

354 $$\sum_{i \in I} h_{ij} y_{ij} \leq cap_j x_j \qquad \forall j \in J \quad (15)$$

355 $$\sum_{j \in J} h_{ij} y_{ij} = \bar{h}_i \qquad \forall i \in I \quad (16)$$

356 $$\sum_{i \in I} h_{ij} y_{ij} = \hat{h}_j \qquad \forall j \in J \quad (17)$$

357 $$p_k^{ij} = \prod_{a=1} P_a \delta_{ak}^{ij} \qquad \forall i \in I,\ j \in J, k \in K \quad (18)$$

358 $$u_k^{ij} = \sum_{a=1} \log P_a \delta_{ak}^{ij} \qquad \forall i \in I,\ j \in J, k \in K \quad (19)$$

359 $$h_{ij} \geq 0 \qquad \forall i \in I,\ j \in J \quad (20)$$

360 $$x_j = \{0,1\} \qquad \forall j \in J \quad (21)$$

361 $$y_{ij} = \{0,1\} \qquad \forall i \in I,\ j \in J \quad (22)$$

362 $$\delta_{ak}^{ij} = \{0,1\} \qquad \forall i \in I,\ j \in J, a \in A \quad (23)$$

According to Eq. (12), at least one shelter facility j must be provided for each disaster node i. Eq. (13) indicates that multiple disaster nodes i can be simultaneously assigned to a single shelter facility j. Eq. (14) indicates that a site must be selected for at least one shelter facility j. In this equation, the maximum number of alternative locations is represented by N. According to Eq. (15), the total capacity of the shelter facility must be greater than or equal to the total number of disaster victims. Eqs. (16) and (17) are conservation constraints for the number of disaster victims. Eq. (18) represents the probability of using path k from disaster node i to shelter facility j. Eq. (19) defines the utility of the risk of following path k from disaster node i to shelter facility j. Eq. (20) indicates that the number of victims traveling from disaster node i to shelter facility j is nonnegative. As indicated by Eq. (21), if shelter facility j has been opened, then $x_j = 1$; otherwise, $x_j = 0$. According to Eq. (22), if disaster victims travel from disaster node i to shelter facility j, then $y_{ij} = 1$; otherwise, $y_{ij} = 0$. As indicated by Eq. (23), if road section a is part of path k, then $\delta_{ak}^{ij} = 1$; otherwise, $\delta_{ak}^{ij} = 0$.

3. Solution algorithm

3.1. Algorithm steps

In the RWGA, random weights are initialized, and an optimal solution is searched

for through the evolution of each weight [8]. However, because this method is susceptible to random values, the quality and efficiency of its solutions can be inconsistent. Therefore, we developed the RRWM, which is based on the RWGA. The RRWM has two components.

In the first component of the RRWM, a fitness function is calculated through a compromise programming method (CPM; [37]), and the adaptive weight approach (AWA; [38]) is used to normalize the values of each objective function. Because the objectives may be in conflict, an approximation of the ideal solution is obtained using the CPM to calculate the distance between the individual solutions and the ideal solution. This approach can be considered an objective search method based on the L_s^k distance function [37, 26]. Moreover, all solutions in the current solution set are used to readjust the weights of each objective by using the AWA. The multiobjective EA is designed to tend toward the global solution. Therefore, the fitness function for a multiobjective problem can be redefined as follows to determine the closest ideal solution based on the CPM and AWA:

$$Z_i^k = \sum_{i=1}^{q} \left(\frac{z_i^{max} - z_i^k}{z_i^{max} - z_i^{min}} \right) \quad \forall \ k \in SOL, \ i \in 1 \sim q \tag{24}$$

where *SOL* is the solution set for the multiobjective problem, q is the number of objectives, and z_i^k is the value of the ith objective function of the kth solution in *SOL*. If objective i is fixed (e.g., i = 1), z_i^k can be considered the result of the standardization of the kth solution in the solution set for objective i. Therefore, we can standardize each objective function as follows:

$$z_i^{norm}(x) = \begin{cases} \dfrac{z_i(x) - z_i^{min}}{z_i^{max} - z_i^{min}}, & if \;\; z_i^{max} > z_i^{min} \\ 0, & if \;\; z_i(x) = z_i^{min} \end{cases} \quad \forall\, i = 1 \sim k,\; x \in P \tag{25}$$

$$z_i^{norm}(x) = \begin{cases} \dfrac{z_i^{max} - z_i(x)}{z_i^{max} - z_i^{min}}, & if \;\; z_i^{max} > z_i^{min} \\ 0, & if \;\; z_i(x) = z_i^{max} \end{cases} \quad \forall\, i = 1 \sim k,\; x \in P \tag{26}$$

$$F(x) = \sum_{i=1}^{k} w_i \cdot z_i^{norm}(x),\; i = 1 \sim k,\; x \in P \tag{27}$$

Eqs. (25)–(27) represent the method for normalizing the values of objective function i for a given solution x. In these equations, $z_i(x)$ and $z_i^{norm}(x)$ denote the values of the ith objective function before and after normalization, respectively, and z_i^{min} and z_i^{max} denote the minimum and maximum values of the ith objective function for solution x before normalization, respectively. After normalization, the values of the objective functions are between 0 and 1. Next, the values of the normalized objective functions are multiplied by their respective weights, and the

results are summed to obtain the fitness value for solution x. The fitness function of the multiobjective problem is presented in Eq. (27).

In the second component of the RRWM, the set of Pareto optimal solutions produced in each generation is adjusted according to the weights randomly generated in the current generation. This effect is reflected in the quality of the current generation's solution and that of the overall multiobjective solution. Therefore, the elitist strategy is adopted to select the superior solution from the set of Pareto optimal solutions in each generation. Finally, the elite Pareto optimal solution set is obtained to normalize the quality of the Pareto optimal solutions. The steps of the RRWM are described as follows:

Step 1: Initiate the algorithm.

Step 2: Calculate the network values.

Based on given postdisaster information, the optimistic evacuation time ($t_{ij,optimistic}$) , the actual evacuation time (t_{ij}) , and the longest evacuation time ($t_{ij,longest}$) between disaster node i and shelter node j is obtained using the shortest path algorithm, and the utility function of perceived evacuation time is derived according to Eq. (4). Moreover, the value of the utility for roadblock risk U_a is obtained according to the

roadblock risk value R_a for each road section a.

Step 3: Encode the network nodes.

Binary gene encoding [0,1] is applied with the decision variable y_{ij} under the assumption that chromosome length is equal to the total number of shelter and disaster nodes, where 0 represents a disaster node and 1 represents a shelter node. Each chromosome represents a feasible solution—a configuration of shelter nodes.

Step 4: Randomly generate an initial population of chromosomes and place the initial population in N_{pop}, and then set the total number of generations T.

Step 5: Evolve the chromosomes.

Confirm whether the chromosomes conform to the model constraints. Next, calculate the values of the objective functions for the chromosomes in N_{pop} that meet these constraints. Normalize these values by using Eqs. (25) and (26). The current Pareto solution set is updated according to these normalized values.

Step 6: Calculate the fitness value.

Eq. (28) is used to obtain the random weights, which are then substituted into Eq. (27) to calculate the fitness value for each chromosome. Subsequently, a linear proportional transformation function [presented in Eq. (29)] is used to calculate p_i.

Next, $N_{pop}/2$ pairs of chromosomes are selected from N_{pop} for mating and mutation.

$$w_i = \frac{random_i(\mathrm{g})}{\sum_{j=1}^{n} random_j(\mathrm{g})}, \quad i = 1, 2, ..., n \tag{28}$$

$$p_i = \frac{z_i - z_{\min}}{\sum_{j=1}^{n} (z_j - z_{\min})} \tag{29}$$

Step 7: Select the elite chromosomes (N_{elite}) from the Pareto optimal solution set.

The chromosomes with the highest fitness values in the Pareto optimal solution set are selected as the elite chromosomes (N_{elite}).

Step 8: Perform mating.

The single-point mating method is applied to the selected chromosomes with a mating rate R_C of 0.8 and randomly selected mating sites. Two new chromosomes are produced, with the mating site serving as the baseline. This mating mechanism yields new chromosomes for the population N_{pop}.

Step 9: Perform mutation.

A certain number of genes in the chromosome are mutated at a mutation rate Rm of 0.06. The selected genes are mutated from 0 to 1 or from 1 to 0.

Step 10: Apply the elitist strategy.

A certain number of N_{elite} chromosomes are randomly removed from the population

N_{pop}. Next, N_{elite} additional chromosomes are randomly selected from the current Pareto optimal solution set and added to N_{pop} to replace the chromosomes that were randomly removed.

Step 11: Terminate the algorithm according to the condition test.

The condition for termination in this model is reaching the maximum number of generations T. If this condition is satisfied, the algorithm is terminated. If the condition is not satisfied, set $t = t + 1$ and return to Step 4.

This algorithm yields a set of elite Pareto optimal solutions, and the most suitable compromise solution can be selected from this set.

3.2. Evaluation of solution sets for the multiobjective problem

In the MOGA, solutions are obtained by approaching the Pareto optimal front through continuous evolution. The present study adopted the assessment of solution sets for the multiobjective problem methods proposed by Zitzler et al. [39]. The solution sets can be evaluated in terms of diversity and convergence. These evaluation methods are described as follows:

1. Convergence of solution sets: Zitzler et al. [39] proposed an evaluation method based on the convergence of solution sets. Assuming that $P', P'' \subseteq P'$ are two

solution sets in the multiobjective space, a mapping from (P', P'') to the interval [0,1] can be used to obtain the coverage rate (CS) of P' and P''. The parameter $CS\ (P', P'')$ is defined as follows:

$$CS\ (P', P'') \triangleq \frac{|\{x'' \in P'' | \exists x' \in P', x' \succ x'' or\ x' = x''\}|}{|P''|} \tag{30}$$

According to Eq. (30), if all solutions x' in P' are dominant or equal to all solutions x'' in P'', then the coverage rate is equal to 1. Thus, the coverage rate is between 0 and 1.

2. Spatial distribution of the solution set: In the present study, three objectives were optimized simultaneously. After being normalized, the objective function values were plotted in a three-dimensional space. The method proposed by Zitzler et al. [39] was used to calculate the spatial distribution of the solution set in the space defined by the normalized objective function values, as presented in Eq. (31). The lower the standard deviation is, the lower the average and minimum distances between members of the solution set are and the more uniform the distribution of the solution set is in the space defined by the normalized objective function values.

$$dtrb = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}\left(\bar{d} - d_i\right)^2} \tag{31}$$

4. Numerical analysis

4.1. Test network data

This study used Zhongzheng District, Taipei City, as a test network. Figure 2 shows that this network contains 31 villages, 153 nodes, and 481 road links. The green nodes represent the 18 existing shelters, such as Zhong-Yi Primary School. The population's temporary shelter requirements due to disaster-induced damage were estimated using the Taiwan Earthquake Loss Estimation System. If a disaster results in 21,452 equivalent number of victims, most people would not have access to shelter. Therefore, 14 alternative shelter sites, such as Chiang Kai-Shek Memorial Hall, were determined, as indicated by the yellow nodes in the figure. The network information is listed in Tables 1 and 2.

4.2.Testing and analysis

In this study, the RRWM was used to solve the multiobjective problem of selecting urban shelter facility sites. The number of selected shelter facilities should not exceed the total number of available sites (i.e., 32). The total number of chromosomes in N_{pop} was set to 500, the number of generations was set to 500, the mating rate R_c was set to 0.8, and the mutation rate R_m was set to 0.06. Key information from the test results is presented subsequently.

With 500 generations, the RRWM was able to search the entire solution space. The total computation time was 249 s, and 500 optimal solution sets were obtained. The minimum adaptive value was 0.58 and was obtained after solution set 340; thus, this set was the superior compromise solution set. The node numbers of the refuge facilities corresponding to the optimal compromise solution included 122, 123, 126, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 143, 144, 147, 148, 149, 150, 152, and 153. According to Eqs. (9)–(11), the total utility of perceived evacuation time was derived as 19257.55 (Objective 1), the total utility of roadblock risk was 67.92 (Objective 2), and the total construction cost was NT$77 million (Objective 3).

Table 3 presents the assignment of victims from disaster to shelter facilities. For example, the equivalent number of victims at node 8 was 235. Because of capacity constraints, 144 equivalent number of victims were assigned to node 132 for shelter. On the basis of the developed allocation mechanism, the remaining 91 equivalent number of victims were assigned to node 140, which exhibited the second-greatest utility of perceived evacuation time. Moreover, node 140 was located near node 132. Overall, the sum of the equivalent number of victims assigned to the different shelter

nodes was equal to the equivalent number of victims at the disaster nodes. Thus, the solution satisfied the constraint for the multiobjective model presented in Eq. (18).

Table 4 shows the sum of the equivalent number of victims from each disaster-affected node to the shelter node, which meets the shelter facilities' limitations for victims. Take Central Culture Park (shelter node 140) as an example, victims from 16 different distasting-affected nodes go to shelter at shelter node 140. the equivalent number of victims was 2,495. It can be seen that all the site selection conditions obtained under multiple objectives meet the capacity constraints of asylum facilities.

4.3. Convergence to the pareto optimal front

This section discusses the coverage rate and spatial distribution of the optimal solution sets. The adaptive values and normalized target values of two elite Pareto optimal solution sets were input into Eq. (30), and a coverage rate of 94% was derived. This result indicates that the new solution was improved relative to the previous solution set. Next, the normalized objective function values (Z_1', Z_2', Z_3') of the Pareto optimal solution set were input into Eq. (31), and a spatial distribution of 0.018972 was obtained. This value indicates the degree to which the nondominated

solutions are uniformly distributed in the three-dimensional space defined by the normalized objective values. We used STATISTICA 6.1 software to plot the spatial distribution of the solution set (Figure 3). The distribution of the solution set near the origin was similar to that of the Pareto optimal front, demonstrating the suitability of the RRWM.

Table 5 presents a comparison of the results of the RRWM, RWGA, and single-objective GA (SOGA). The performance of the optimal solution set obtained using the RRWM was further evaluated. Eight weight values from the SOGA were tested. The number of solution sets (N_{pop}) and the number of generations were 500 for the RRWM, RWGA, and SOGA. Table 5 lists the adaptation values, spatial distributions, and coverage rates of the aforementioned algorithms. First, Eqs. (25) and (26) were used to derive the RRWM fitness value of 0.58, which was superior (lower) to those obtained using the other algorithms. Second, the coverage rate of the RRWM reached 94%, and its spatial distribution was 0.018972. In contrast to the RWGA and SOGA, the RRWM achieved robust convergence in terms of solution performance and coverage rate.

Furthermore, on the basis of the state of the scatter diagram. In Figure 4, the

distribution of the solution set obtained by RWGA does not form a Pareto front. As for The spatial distribution of the SOGA was optimized with weights of 0.92, 0.04, and 0.04 (as shown in Figure 5). However, this solution set was not forming a Pareto frontier either. By contrast, the spatial distribution value of the RRWM was suboptimal; however, the solution set was close to a Pareto optimal front when plotted in the space defined by the normalized objective function values. Moreover, the solution set of the RWGA was oriented in the direction of the Z_1'-axis with a suboptimal spatial distribution. For other weighting strategies, the solution sets were oriented in the direction of the axis with the highest enactment value (i.e., aligned according to the specific weight ratio).

5. Conclusions and recommendations for future work

This study presents a model for site selection for shelter facilities after large-scale urban disasters. A trade-off exists among the utility of perceived evacuation time, the utility of roadblock risk, and the cost of shelter construction. Accordingly, the relationships between these parameters were modeled using a multiobjective model. The locations selected for shelter facilities should be the optimal compromise between the aforementioned parameters. The number of people required to move from disaster nodes to shelter nodes and the capacities of the shelter facilities are also included in

the developed model.

In contrast to the RWGA, the proposed RRWM includes an elitist mechanism and is designed to evolve an evenly distributed trade-off frontier defined by nonconvex functions. The RRWM yields a nondominated solution set with satisfactory distribution; hence, it may provide valuable assistance to decision-makers. This finding demonstrates the flexibility of the proposed method for practical planning problems and its effectiveness for evaluating decision schemes.

This study was limited to a single category of displaced people. In the future, different identities can be included to solve problems cause by multiple identities. Information on the utility of perceived evacuation time and the utility of roadblock risk can be collected during regular household surveys and urban environmental audits. The main focus of the present study was on modeling and algorithm design. In future studies, the proposed model can be applied and evaluated by adding parameters after calibration to ensure that the results are more suited to practical requirements.

Declarations

Availability of data and materials

All data generated or analysed during this study are included in this published article.

Competing interests

To the best of our knowledge, the named authors have no conflict of interest, financial or otherwise.

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Authors' contributions

Conception and design: KCY, Provision of study materials: KCY; WC; WCS, Collection and assembly of data: WC; WCS, Data analysis and interpretation: KCY; WC, Manuscript writing: All authors.

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Table 1 Network details for Zhongzheng district, Taipei City.

Node	Facilities	Capacity	Setting cost	Node	Facilities	Capacity	Setting

numbe r		(Equivalen t population)	(NT$ million)	numbe r		(Equivalen t population)	cost (NT$ ten thousand)
122	Zhongyi Elem. Sch.	330	200	138	Mandarin Experimenta l Elementary School	269	100
123	Yingqiao Junior High School	282	100	139	Yingqiao Elementary School	303	100
124	Affiliated Experimenta l Elementary School	387	200	140	Central Culture Park	3355	1000
125	Hongdao Junior High	317	100	141	Qidong Park	360	300

	School						
126	228 Memorial Park	5824	800	142	Zhongxiao Park	380	300
127	Zhongzheng Sports Center	480	300	143	Wenguang Park	390	300
128	Zhongzheng Junior High School	530	400	144	Chiang Kai-Shek Memorial Hall	5109	1000
129	Taipei First Girls High School	290	100	145	Xinai Park	470	400
130	Guting Junior High school	296	100	146	Lianyun Park	390	300

131	Chenggong High School	280	100	147	Yongchang Park	380	300
132	Zhongxiao Elementary School	280	100	148	Yingqiao Park	290	200
133	Dongmen Elementary School	330	200	149	Nanchang Park	760	600
134	He-Ti Elementary School	320	100	150	Guling Park	510	400
135	Nanmen Elementary School	320	100	151	Wensheng Park	320	200
136	Nanmen Junior High School	371	200	152	Treasure Hill Temple	5109	1000

137	Jianguo High School	520	400	153	Liming Park	280	200

Table 2 List of affected nodes.

Node number	Equivalent number of victims	Node number	Equivalent number of victims	Node number	Equivalent number of victims	Node number	Equivalent number of victims	Node number	Equivalent number of victims
1	125	25	261	49	246	73	125	97	255
2	225	26	195	50	146	74	212	98	276
3	115	27	205	51	279	75	117	99	197
4	195	28	105	52	179	76	151	100	139
5	251	29	145	53	199	77	161	101	175
6	232	30	181	54	198	78	261	102	254
7	132	31	281	55	196	79	197	103	197
8	235	32	181	56	289	80	199	104	239
9	136	33	213	57	177	81	252	105	20

10	135	34	113	58	277	82	182	106	21
11	225	35	161	59	177	83	184	107	175
12	125	36	205	60	146	84	182	108	230
13	225	37	105	61	140	85	182	109	132
14	154	38	205	62	179	86	182	110	132
15	254	39	244	63	273	87	222	111	165
16	195	40	144	64	147	88	139	112	165
17	177	41	191	65	182	89	105	113	54
18	277	42	118	66	182	90	205	114	53
19	177	43	197	67	162	91	154	115	51
20	136	44	198	68	122	92	197	116	52
21	225	45	164	69	222	93	198	117	165
22	125	46	264	70	179	94	239	118	94
23	254	47	164	71	125	95	122	119	93
24	161	48	164	72	225	96	222	120	93
								121	93

Table 3 Assignment of victims from disaster nodes to shelter facilities.

Affected node	Victims of equivalent	Shelter facility node	Equivalent victims of shelter
8	235	132	144
		140	91
25	261	126	142
		153	119
27	205	131	103
		140	102
50	146	143	144
		140	2
51	279	129	92
		144	187
57	177	133	66
		144	111
64	147	135	47
		126	100
66	182	126	19

		144	163
		136	67
70	179		
		144	112
		148	185
72	225		
		144	40
		122	205
74	212		
		149	7
		138	152
80	199		
		149	47
		149	4
82	182		
		144	178
		137	117
88	139		
		150	22
		150	63
92	197		
		144	134
		147	183
93	198		
		144	15

		139	64
95	122		
		144	58
		134	44
101	175		
		152	131
		130	99
104	239		
		144	140
		123	150
111	165		
		152	15

721

722 **Table 4** Relationship between the holding status and capacity limits of shelter
723 facilities.

Affected node → Refuge node	Total equivalent number of displaced victims	Capacity of shelter facility
3 → 140 (115)		
4 → 140 (195)		
5 → 140 (251)	2495	3355
6 → 140 (232)		
7 → 140 (132)		

Affected node → Refuge node	Total equivalent number of displaced victims	Capacity of shelter facility
8 → 140 (91)		
9 → 140 (136)		
10 → 140 (135)		
16 → 140 (195)		
18 → 140 (277)		
27 → 140 (102)		
28 → 140 (105)		
29 → 140 (145)		
38 → 140 (205)		
50 → 140 (2)		
19 → 140 (177)		
84 → 150 (182)		
88 → 150 (22)		
	510	510
92 → 150 (63)		
96 → 150 (222)		

Affected node → Refuge node	Total equivalent number of displaced victims	Capacity of shelter facility
106 → 150	(21)	

Equivalent information on the number of disaster victims is presented in parentheses

Table 5 Comparison of the convergence of different algorithms.

Applied algorithms	Weights of w_1, w_2, w_3	Fitness value	Distribution of space	Cover value	CPU time (s)
RRWM	Random weights	0.58	0.018972	0.94	248.82
RWGA	Random weights	1.01	0.045126	0.97	248.82
SOGA	0.92 : 0.04 : 0.04	0.91	0.011198	0.90	319.02
	0.04 : 0.92 : 0.04	0.81	0.036868	0.97	270.66
	0.04 : 0.04 :	0.77	0.043224	0.81	296.52

Applied algorithms	Weights of w_1, w_2, w_3	Fitness value	Distribution of space	Cover value	CPU time (s)
	0.92				
	0.96 : 0.02 : 0.02	0.59	0.047214	0.93	271.38
	0.02 : 0.96 : 0.02	0.61	0.038667	0.97	269.04
	0.02 : 0.02 : 0.96	0.79	0.038329	0.81	256.80
	0.98 : 0.01 : 0.01	0.62	0.043297	0.95	271.02
	0.01: 0.01: 0.98	0.79	0.037097	0.63	252.54

Figure captions

Fig. 1 Perceived utility function of evacuation time

Fig. 2 Network for Zhongzheng District, Taipei City

Fig. 3 Spatial distribution of the RRWM solution set

Fig. 4 Spatial distribution of the RWGA solution set

Fig. 5 Spatial distribution of the SOGA solution set under different target weights

Figures

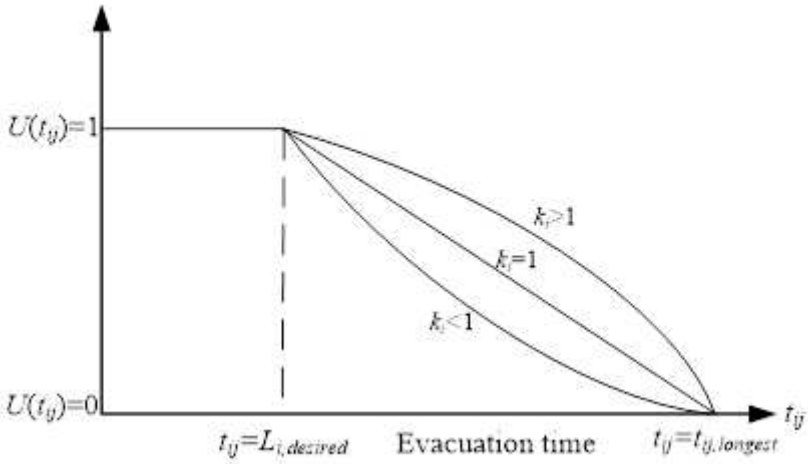

Figure 1

Perceived utility function of evacuation time

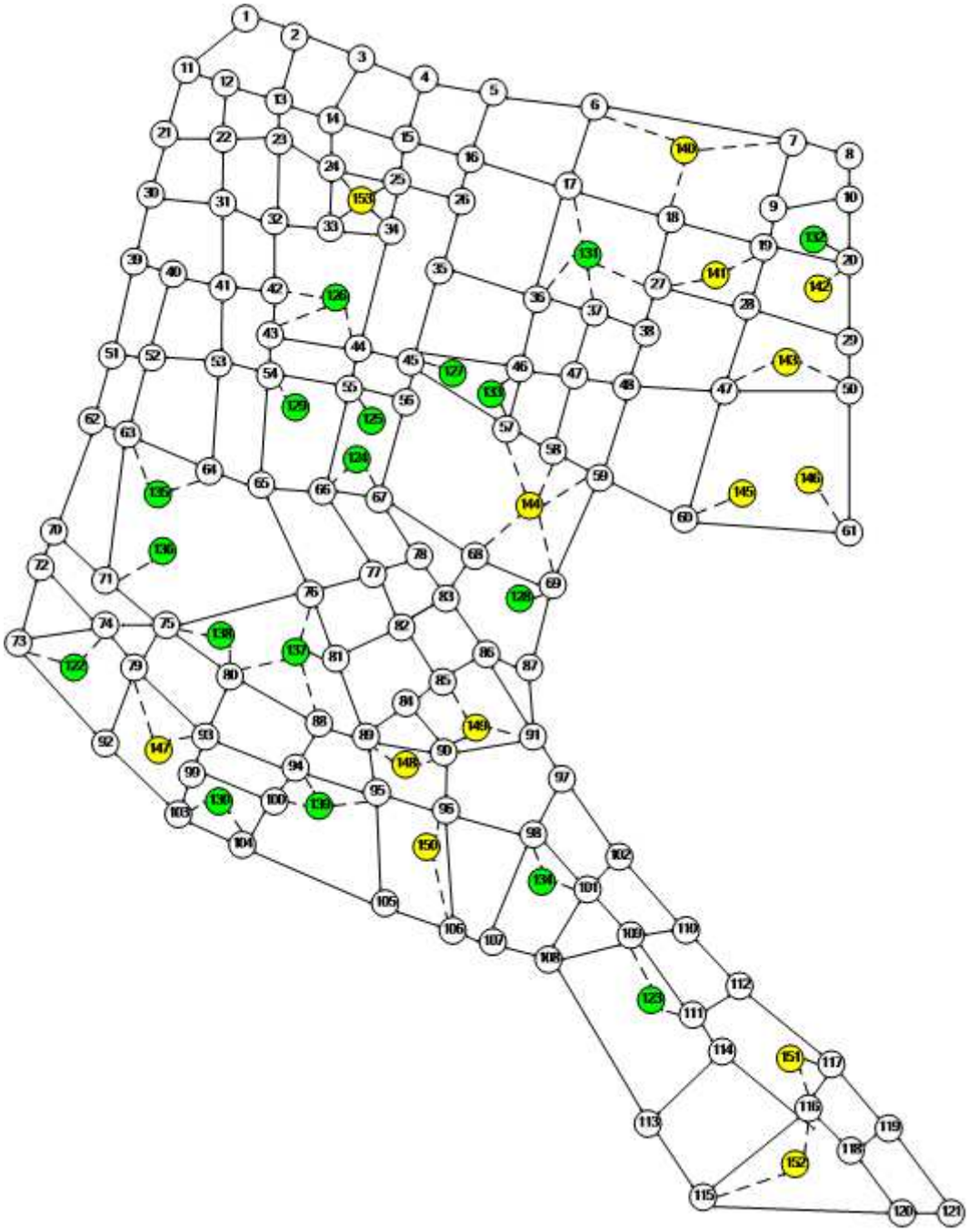

Figure 2

Network for Zhongzheng District, Taipei City

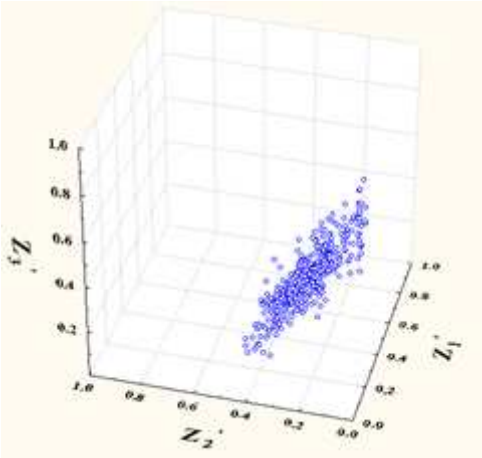

Figure 3

Spatial distribution of the RRWM solution set

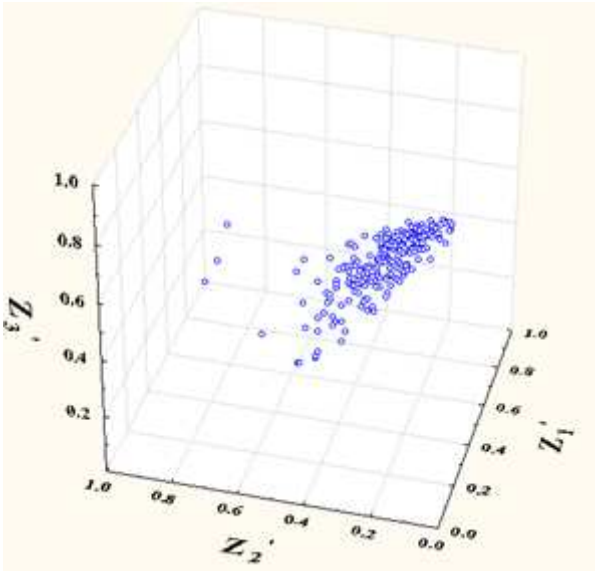

Figure 4

Spatial distribution of the RWGA solution set

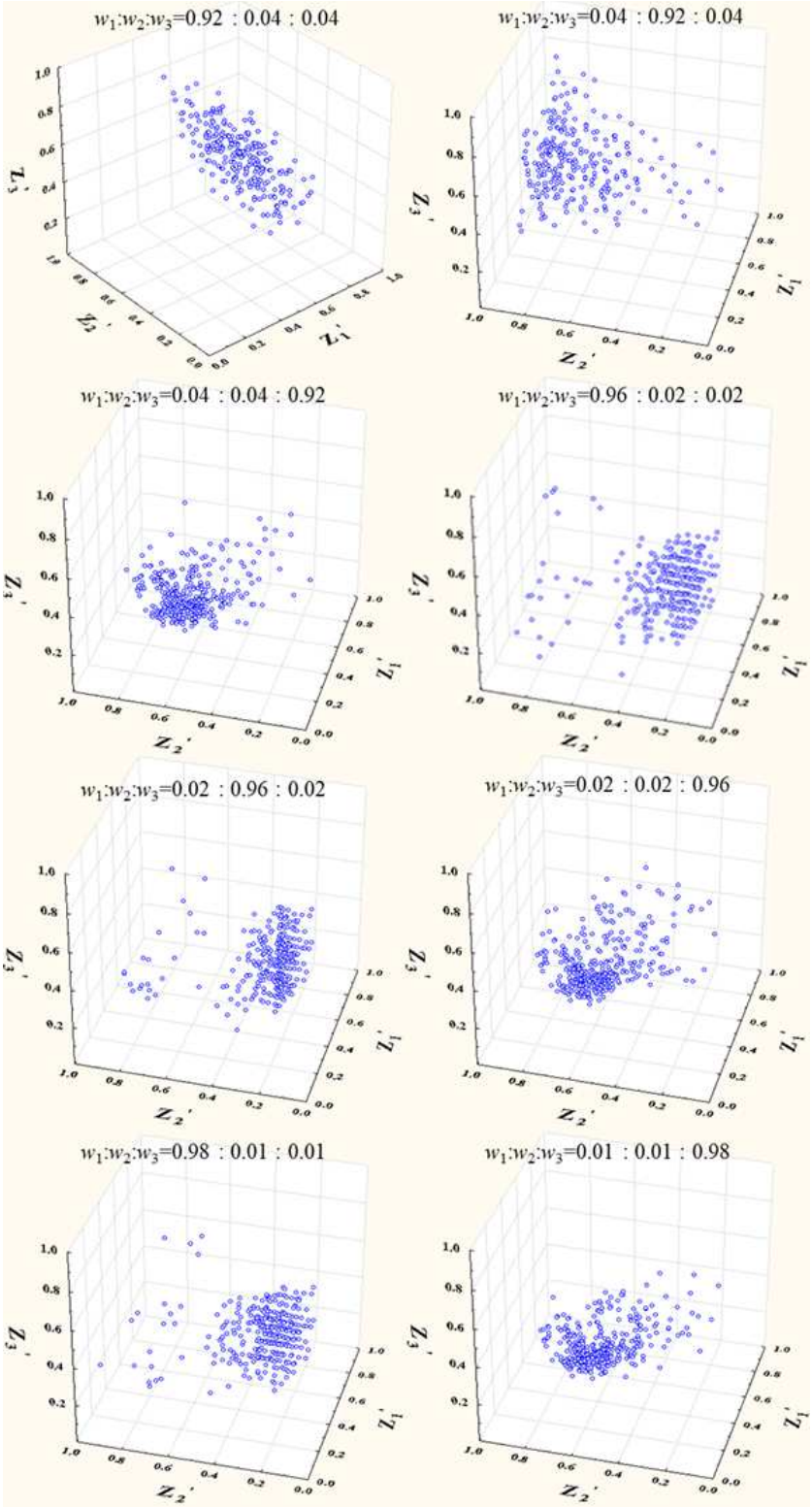

Figure 5

Spatial distribution of the SOGA solution set under different target weights